Environmental Engineering and Management Journal July 2021, Vol. 20, No. 7, 1077-1085
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

"Gheorghe Asachi" Technical University of Iasi, Romania

ESTIMATION OF SOIL ORGANIC CARBON DISTRIBUTION BY GEOSTATISTICAL AND DETERMINISTIC INTERPOLATION METHODS: A CASE STUDY OF THE SOUTHEASTERN SOILS OF NIGERIA

John Kingsley[1]*, Sunday Marcus Afu[2], Isong Abraham Isong[2], Prince Ageyman Chapman[1], Ndiye Michael Kebonye[1], Esther Okon Ayito[2]

[1]Department of Soil Science and Soil Protection, Faculty of Agrobiology, Food and Natural Resources, Czech University of Life Sciences Prague, Kamýcká 129, 165 00 Praha, Suchdol, Prague, Czech Republic
[2]Department of Soil Science, Faculty of Agriculture, University of Calabar, PMB 1115, Calabar-Nigeria

Abstract

Soil organic carbon (SOC) plays a significant role in ecosystem protection and sustainable agriculture. The present study aims to estimate the spatial distribution of SOC using three different interpolation methods: ordinary kriging (OK), cokriging (COK), and inverse distance weighting (IDW). Sixty (n = 60) soil samples were collected from the depth of 0–30 cm and analyzed for SOC. The digital elevation model of the site was obtained from USGS explorer at 30 m spatial resolution and processed. Ten (10) terrain attributes were obtained, and a correlation matrix was conducted between SOC and terrain derivatives. The whole dataset was used to evaluate the model accuracy; root mean square error (RMSE) and mean error (ME) were the criteria adopted. Mean value of the SOC of the study area was generally low when compared to the standard rating for tropical soils (< 2%). SOC was significantly ($p < 0.01$) correlated with LS-factor ($r = 0.34$*), negatively correlated with elevation ($r = –0.30$*) and profile curvature ($r = –0.30$*). IDW performed better (RMSE = 0.75, ME = –0.004) followed by OK (RMSE= 0.78, ME = –0.004) and then COK (RMSE = 0.94, ME = –0.067). Conversely, COK produced the model with the smallest ME with terrain attributes (elevation, LS-factor, and profile curvature). The findings in the study showed that IDW is superior in SOC estimation. COK with the terrain attributes proved to have the capacity as a useful ancillary variable for improving the spatial structure of SOC maps of southeastern Nigeria.

Key words: interpolation, kriging, soil organic carbon, tropical soils

Received: August, 2020; Revised final: November, 2020; Accepted: December, 2020; Published in final edited form: July, 2021

1. Introduction

The importance of estimating spatial soil organic carbon in the biosphere ranges from agricultural productivity to environmental sustainability (Forkuor et al., 2017; Wiesmeier et al., 2014). SOC plays a vital role in sustainable soil fertility, soil quality and wellbeing (Gregorich et al., 1994). SOC controls most soil properties such as porosity, aggregations of particle sizes, moisture retention, and retaining the basic cations in the soil solution (USDA-NRCS, 1995). The SOC stock of the soils of southeastern Nigeria contributes about 0.2 to 30.8 Mg C ha^{-1} to Nigeria's SOC stock (Akpa et al., 2014). The southeastern regions of Nigeria are dominated by agroforestry production, and this agricultural production system can increase carbon stock in the soils through tree biomass under the humid tropical climatic condition. However, there is the challenge of SOC loss which is induced by the adverse effect of climate change (Wiesmeier et al., 2014). SOC content spatially varies over different

* Author to whom all correspondence should be addressed: e-mail: johnk@af.czu.cz; Phone:+420777871317

agricultural and climatic zones, and there is a need to produce SOC maps for each zone for sustainable agricultural productivity (Liu et al., 2014). More so, quantifying the spatial variability of soil carbon will explain the land ecosystem and establish a baseline for others to calculate the rates of SOC change imposed by management practices (Sanderman and Baldock, 2010).

However, quantifying SOC stocks at a point location is difficult due to the high spatial variability in a given soil unit (Cerri et al., 2000), caused by several soil-forming factors and environmental covariates (Fang et al., 2012). This place demands on the spatial representation of soil organic carbon through regional studies that aids in refining global assessments obtained through regional data (Wang et al., 2010), which is aided through geostatistical and GIS representation (Piccini et al., 2014). This advanced technique emphasizes the benefits of digital soil mapping, which is cost-effective compared to conventional soil mapping in providing soil inventory in formats usable by different soil users. This approach in soil science is referred to as *Pedometrics*, which is a branch of soil science that applies geostatistics, fuzzy membership, pedotransfter functions, and classification trees in soil studies (Mcbratney et al., 2003; Zhu et al., 2010).

Various geostatistical and machine learning techniques have been utilized in the previous to model the spatial distribution of SOC (Kumar et al., 2013). Traditional measures might not make out the spatial allotment of soil properties in the unsampled areas. On the other hand, geostatistics with deterministic models are productive techniques used for examining the spatial differences of soil properties and their irregularity by lessening the fluctuation of evaluation mistake and execution costs (Bhunia et al., 2016). Past studies have utilized geospatial procedures to assess spatial affiliation in soils and to assess soil properties' environmental variability. Besides, more researchers have assessed the expectation exactness of SOC by comparing different modelling approach such as multiple linear regression, random forest, cubist, kriging, inverse distance weighted, empirical Bayesian kriging and so on (Mondal et al., 2016). Mohammad et al. (2010), in their prediction study, stated that ordinary kriging (OK) and cokriging techniques gave better prediction results when compared to the deterministic method [e.g. inverse distance weighting (IDW)] technique for the prediction of the spatial distribution of soil properties. Also, Pang et al. (2011) stated that OK is the foremost common sort of geostatistical technique used in evaluating and modelling surface maps of soil properties.

In spite of the broadly utilized approach in mapping soil properties over the final decades (Zhang et al., 2017), the use of geostatistics techniques and other predictive models to carry soil inventory in Nigeria is constrained (John et al., 2019b). Too, there's small to no evaluated nearby maps in Nigeria. Thus the soaring request for this research for proper soil management and policymaking. The strategies embraced in this study is due to the reality, there's no particular method that predicts SOC with the leading precision (Mondal et al., 2016).

Southeastern Nigeria's is situated in the humid tropical agro-ecological zone of the country. Soils of the region are highly weathered, dominated by massive sand mixed with low silt and clays fractions (John et al., 2018). Furthermore, in Nigeria, land evaluation and soil nutrient assessment are quite old and outdated. And regardless of the progress in the usage of digital soil mapping (DSM) techniques in regions of the world, little to no research has considered the use of DSM to explain soil nutrient variability in southeastern Nigeria. However, the conventional soil quality assessment method depends on a random soil sampling procedure to acquire an approximated soil fertility status value for a farmer's field (Ayito et al., 2018; Yang et al., 2014). This approach overlooks spatial variability, and the conventional soil laboratory analysis results do not provide randomness of variations obtained from different sampling points. Therefore, some parts of the field may receive excess fertilizer, while others may lack nutrients and experience insufficient productivity levels.

The objective of this study was to estimate SOC distribution using three modelling techniques such as OK and COK and IDW interpolations in soils of southeastern Nigeria.

2. Material and methods

2.1. Description of the study location

The research was conducted in a consistently steady landscape of Awi in the Akamkpa Area of Cross River State, Nigeria. The research area is situated on 5°22'27.26"N and 8°26'28.39"E for latitude and longitude, respectively (Fig. 1). The site's size is approximately 71.9 hectares on about 180 m high terrain above mean sea level (AMSL). "The area's rainfall and relative humidity ranged between 1500 to 3500 mm and 80 to 90% per year, while the mean annual temperature ranged from 25.4 to 27.5°C (NiMet, 2015)". "The vegetation of the study area is predominantly secondary forest re-growth. Lithologically, the Awi area is underlain by about 40% of the sedimentary basins, occupying roughly 10,000 km^2 of Southeast States (Ekwueme et al., 1990)". According to John et al. (2019), the soils of the area are high in sand, but low in silts and clay contents. "Taxonomically, the soil order of the site is predominantly Ultisols, and the soil classified as Typic paleudults (Aki et al., 2014; John et al., 2019b).

2.2. Soil sampling and laboratory analysis

A total of sixty (n = 60) composite samples were collected through stratified random sampling. Samples were collected at a depth of 0 – 30 cm with the aid of a soil auger.

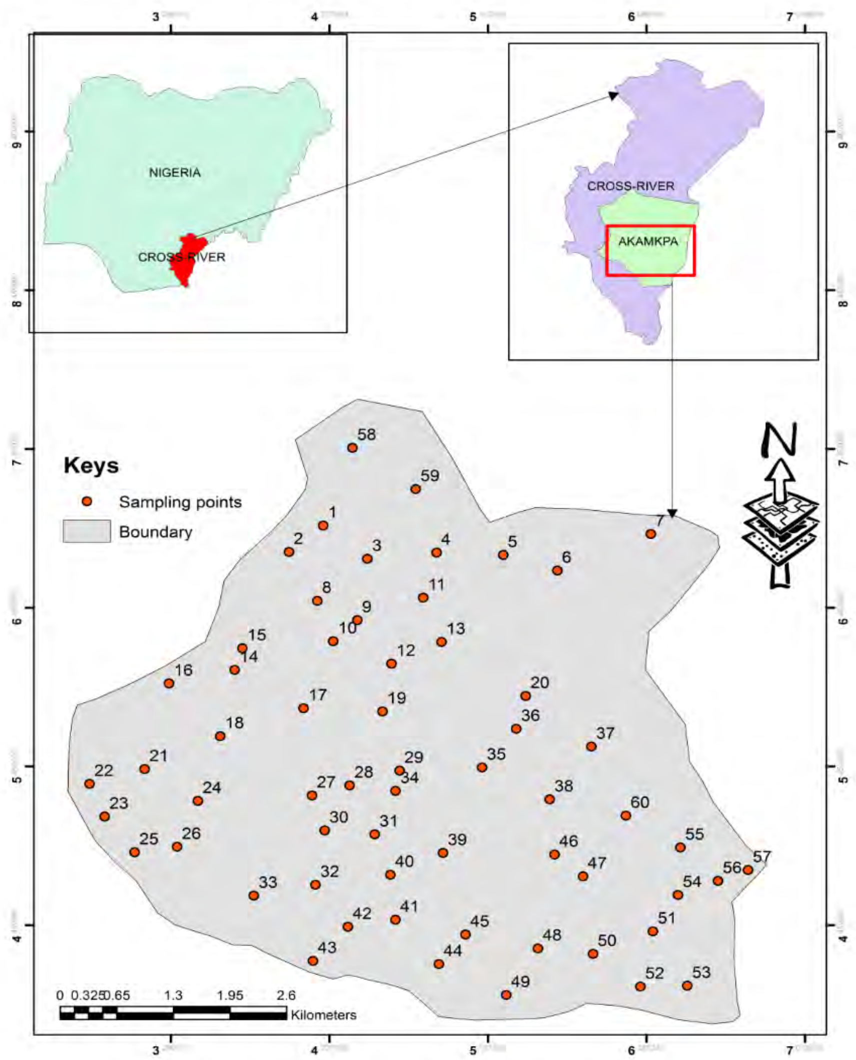


Fig. 1. Map of Awi study site showing the different auger points (n = 60)

Each sample location was labelled and recorded with a hand-held global positioning system (GPS).The samples were taken to the laboratory, air-dried, ground, and sieved with a 0.5 mm mesh. SOC was determined by the standard Walkley-Black wet oxidation method using acid dichromate ($K_2Cr_2O_7$) solution, as outlined in (Udo et al., 2009). This analysis was carried out at the University of Calabar Soil Science Laboratory, as presented in (Eq. 1).

$$\%SOC = N\left(V1 - V2\right)0.3f/w \tag{1}$$

where: N = Normality of $K_2Cr_2O_7$ solution; $V1$ = ml ferrous ammonium sulphate required for the blank; $V2$ = ml ferrous ammonium sulphate needed for the sample; w = sample in 1 gram.

2.3. Terrain model

Digital elevation model (DEM) was obtained from Shuttle Radar Topography Mission (SRTM) at the resolution of 30 x 30 m from and processed in SAGA-GIS (Olaya, 2004). "The following terrain attributes were obtained, analytical hillshadding (Ah), slope (S), aspect (As), plan curvature (Plan C), profile curvature (Profile C), convergence index (CI), topographic wetness index (TWI), LS factor (LS-F), channel network base level, channel network distance (CND), valley depth (VD) and relative slope position (RSP).

2.4. Correlation between SOC and terrain attributes

The Pearson correlation coefficient (PCC) is one of the most established effect-size indicators, in part because of its role as a validity coefficient (Morris, 2007). It takes values between the range of −1 to +1, all-encompassing, and yields a measure of the strength of the linear relationship that exists between two variables. Furthermore, for the purpose of this current study, we only considered terrain attributes that showed a significant correlation ($p < 0.001, 0.01, 0.1$) with SOC and observed to influence its variability in the study location. These terrain attributes were incorporated into the COK model.

2.5. Spatial modelling for estimating soil organic carbon

2.5.1. Geostatistical technique

The geostatistical method uses unbiased predictions with minimum variance for the targeted soil property (Stein and Corsten, 1991). OK, and COK is among the various types of geostatistical methods. The OK process uses an estimated mean of a particular soil property at a known location to predict the value at an unsampled location (Bishop and McBratney, 2001; Goovaerts, 1997; Grunwald et al., 2008) (Eq. 2), whereas COK uses information on several variable types to predict a particular target variable (in this case SOC). And these variables must exhibit a strong relationship with the targeted property (Bivand et al., 2008; Tziachris et al., 2017).

$$Z'(x_0) = \sum_{i=1}^{n} \lambda . Z(x_i) \tag{2}$$

where: $Z'(x_0)$ is the predicted/interpolated value for point x_0, $Z(x_i)$ is the known value, and λ_i is the kriging weight for the $Z(x_i)$ values. It can be calculated by the semi-variance function of the variables on the condition that the estimated value is unbiased and optimal (Eq. 3).

$$\gamma(h) = 1 \big/ 2N(h) \sum_{i=1}^{n} \left[Z(x_i) - Z(x_i + h) \right]^2 \tag{3}$$

where: γ *(h)* is the semi-variance, *N(h)* is the point group number at distance h, $Z(x_i)$ is the numerical value at position x_i, and $Z(x_i + h)$ is the numerical value at a distance $(x_i + h)$."

2.5.2. Deterministic technique

IDW is a deterministic predictive tool that determines cell values using a linearly weighted combination of a set of sample points and where the weight is a function of inverse distance (Philip and Watson, 1982; Bhunia et al., 2016; Liu et al., 2017). Estimated values were interpolated based on the data from surrounding locations using the Eqs. (4-5).

$$Z(x_o) = \sum_{i-1}^{n} w_i Z(x_i) \tag{4}$$

where: *Z(x0)* is the estimated value, *wi* is the weight assigned to the value at each location *Z (χi), n* is the number of close neighbouring sampled data points used for estimation.

The weights were estimated using Eq. (5):

$$w_i = 1 \big/ d_i^{\,p} \Big/ \sum_{i=1}^{n} 1 \big/ d_i^{\,p} \tag{5}$$

where: d_i is the distance between the estimated point and the sample point, *p* is an exponent parameter.

2.6. Model validation of the spatial soil organic carbon estimation

In the evaluation of our spatial estimation, we used the total data to estimate the trend and autocorrelation of our models. "The interpolated result was then extracted to the whole data points. Root mean square error (RMSE) and mean error (ME). The RMSE gives an estimate of the standard deviation of the residuals (prediction errors)." While mean error (ME) is taken as the mean of residuals, it calculates the deviation of the predicted value Eqs. (6-7) expresses them as:

$$RMSE = \sqrt{1 \big/ n \sum_{i=1}^{n} (p_i - o_i)^2} \tag{6}$$

$$ME = 1 \big/ n \sum_{i=1}^{n} (p_i - o_i)^2 \tag{7}$$

where: *pi* = predicted values, *oi* = observed values, *n* = the number of validation points. Interpretatively, a good model should have a low RMSE and ME close to 0 if the predicted results are unbiased (Robinson and Metternicht, 2006).

2.7. Data analysis

SOC spatial maps were produced via ArcGIS.Terrain attributes were derived through System for Automated Geoscientific Geographical Information System (SAGA-GIS) software. At the same time, discrete statistics and estimate the correlation matrix between SOC and terrain attributes processed via R studio.

3. Results and discussion

3.1. Descriptive statistics

The samples summary statistics of SOC and terrain attributes are presented in Tables 1-2, respectively. The result revealed that the SOC value of the area ranged from 0.7–3.2%, with a mean of 1.77%. SOC was very low when compared with Landon (1991) rating for tropical soils. The result obtained here is similar to the report of John and Akpan-Idiok (2019b) and in contrast with that Abua and Eyo (2013) and Aki et al. (2014). They rated moderate SOC in similar soils. Furthermore, the low SOC obtained in this study may be attributed to surface runoff (Larsen et al., 2014), high temperature and precipitation (Bolliger et al., 2006), increased soil acidity (John et al., 2019a) and intensive cropping without adequate nutrient management (Ayito et al., 2018). The measured SOC expressed a normal distribution with high variability (CV=37.8), a positive skewness of 0.39, and a kurtosis of 2.15. On the other hand, the terrain attributes showed a normal distribution and were not transformed as well. However, LS-F, Profile C, CND and VD produced high variability with CV values of 37.8, 38, 928.9, 37.62 and 37.56, respectively, compared to the standard rating outlined by Gubiani et al. (2011). Simultaneously, RSP and Elev yielded moderate and low variability with CV values of 22.85 and 3.3, respectively.

Table 1. Descriptive statistics of SOC

Variables	*Mean*	*Min*	*Max*	*SD*	*CV*	*Skewness*	*Kurtosis*	*Data Transformation*
SOC (%)	1.77	0.7	3.2	0.67	37.8	0.39	2.15	None

Table 2. Descriptive statistics of some selected terrain attributes

	Elev (m)	*LS-F*	*RSP*	*Profile C*	*CND*	*VD*
Mean	165.9	2.10	0.50	651383.04	13.37	13.26
Standard Deviation	5.46	0.48	0.19	6050954.93	5.03	4.98
Kurtosis	2.30	4.55	-0.51	-0.49	-0.45	-0.53
Skewness	0.19	1.99	0.32	0.02	0.35	-0.31
Minimum	155.20	1.55	0.10	-14546609.78	2.68	1.54
Maximum	178.41	3.91	0.94	14363443.95	25.40	23.87
CV	0.19	22.85	38	928.90	37.62	37.56
Confidence Level(95%)	1.41	0.12	0.05	1563127.41	1.30	1.29
Data Transformation	None	None	None	None	None	None

Elev = Elevation; LS-F = LS-factor; RSP = Relative Slope Position Profile C= Profile Curvature; CND = Channel Network Distance; VD = Valley Depth

Generally, the variables were employed untransformed for the modelling purpose.

3.2. Correlation between SOC and terrain attributes

A Pearson correlation analysis was estimated to explain the relationship between SOC with the terrain attributes (Fig. 2). The result revealed that SOC was negative and significantly ($p < 0.01$) correlated with Elev ($r = –0.30$*), RSP ($r = –0.29$*), CND ($r = –0.29$*), Profile C ($r = –0.30$*) but positively and significantly correlated with LS-factor ($r = 0.34$*). The result further revealed that LS-factor was the highest terrain attributes that yielded the highest correlation with SOC compared to other terrain attributes. The negative and significant ($p < 0.01$) correlation obtained between SOC and Elev is similar to the report by Kozłowski and Komisarek (2018).

Also, the same report was not consistent with the result obtained for SOC and Profile C in our study. Furthermore, the result of our study corroborates with that of Li et al. (2018), who observed significant correlations between SOC and LS-factor, Profile C, and other terrain derivatives. In this study, the Pearson correlation coefficient presented the relationship between SOC and terrain attributes. It revealed the capability of estimating SOC variability via terrain attributes. In the COK modelling, terrain attributes with relatively high correlation were used. These terrain attributes include LS-F, Elev, and Profile C as they could improve the prediction of SOC OC in the local landscape of southeastern Nigeria.

3.3. Spatial estimation of SOC

In this present study, OK, COK and IDW methods were used to estimate the spatial variability of SOC. Discrete statistics of the interpolation output is presented in Table 2, while the fitted semivariograms for the OK and COK model are shown (Fig. 3a -b). The Semivariogram model revealed that OK and COK produced a stable model. OK was fitted with nugget = 0.19, sill = 0.42 and range = 1.998 while COK was fitted with nugget = 0.28, sill = 0.30 and range = 1.997. On the other hand, COK presented a high nugget effect (0.28) compared to OK (0.19). Elev, LS-F, and Profile C may have contributed to this variation as they have been reported to influence SOC spatial variability (Wu et al., 2009; Tsui et al., 2013).

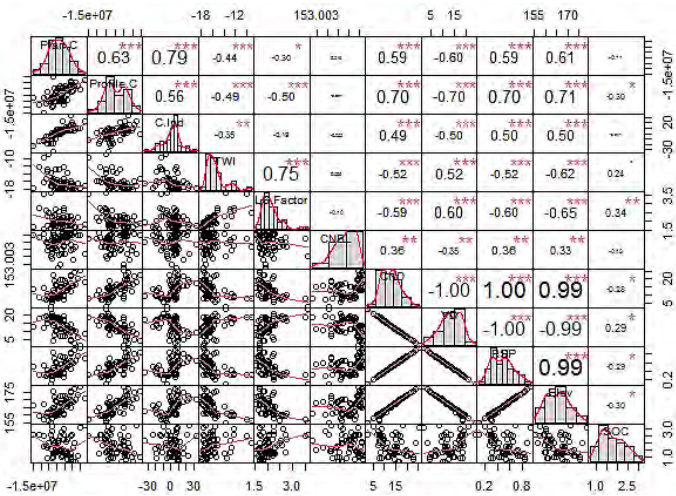
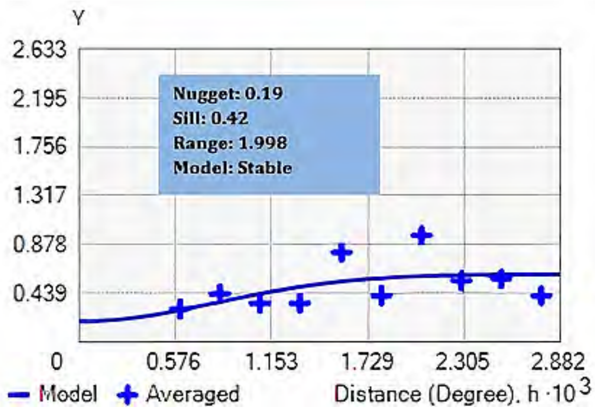
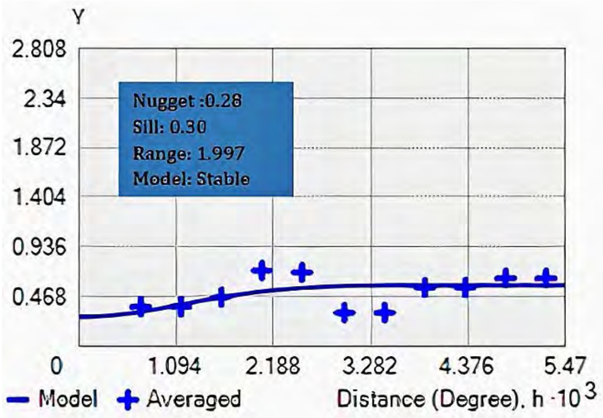


Fig. 2. Correlation matrix of SOC and terrain derivatives



(a)



(b)

Fig. 3. (a) OK semivariogram (b) COK semivariogram

The spatial autocorrelation for OK and COK was 31.1% and 48.2%, respectively. Spatial autocorrelation is the nugget to sill ratio as defined by Cambardella et al. (1994). The values obtained for OK and COK showed that the models gave a moderate spatial autocorrelation as they fell within (> 25% < 75%), a criterion by Cambardella et al. (1994). The variation of SOC seen in the site may be associated with the accumulation of mineral and organic material from relative slope positions, as suggested by Brodsky et al. (2013).

3.4. Comparison of OK, COK and IDW interpolation

In evaluating the model with the best performance, the whole dataset was employed. The criteria for the best model was a low RMSE and ME value (Yang et al., 2009). As shown in Table 3, OK (RMSE = 0.78, ME = –0.004), COK (RMSE = 0.94, ME = –0.067) and IDW (RMSE = 0.75, ME = -0.004). The results revealed that the ME values of the three methods were close to 0, indicating that predicted values were unbiased. Furthermore, the cross-validation result presented in Table 2 revealed that IDW was more accurate than both OK and COK having the lowest RMSE value. The OK model followed the IDW as the next model with a low RMSE. IDW as the best model agrees with Li and Heap (2008) and contrasts with Bhunia et al. (2016). COK, on the other hand, yielded a smaller mean error compared to OK and IDW. The narrow mean error obtained may be attributed to the added terrain attributes (Elev, LS-factor and profile C).

COK model also suggests that terrain attributes could serve as excellent auxiliary variables for improving the reliability of spatial SOC prediction. The result obtained here is similar to the report by Yang et al. (2014), who reported the importance of elevation and slope in estimating SOC variability in Southwest China. Also, Triantafilis et al. (2001), Wu et al. (2009), Tziachris et al. (2017), and Saleh (2018) reported a low mean error for COK. Besides that, Chabala et al. (2017) and Bhunia et al. (2016) reported OK as the best model for SOC prediction in their studies. Nevertheless, comparative interpolation studies of SOC prediction have always shown mixed results, often associated with available data and the type of interpolation technique (Chabala et al., 2017).

3.5. Prediction maps of SOC by the different interpolation methods

SOC predicted maps using OK, COK and IDW models are presented in Fig. 4. The maps structures showed significant differences, revealing a high spatial variability in SOC. The map developed from OK was smoother than that produced from COK and IDW, respectively.

COK, as well as IDW, revealed more details in local areas as compared. The result obtained in the predicted map of OK corroborates with the report by Wu et al., (2009), who reported a smooth trend in the OK map of soil organic matter.

The predicted SOC map by OK was less spatially detailed (i.e. evenly distributed) than that by COK and IDW in some local regions, such as the central part in the study site, as shown in the SOC prediction maps (Fig. 4 (a-c)). SOC ranged from 0.98-2.64%, 1.18–2.32% and 0.70–3.2% in OK, COK and IDW maps, respectively. Generally, the predicted SOC maps revealed that SOC was relatively high in the central part of the research area.

Table 3. Comparison of the interpolation methods to map SOC distribution

Interpolation methods	*RMSE (%)*	*ME*
OK	0.78	-0.004
COK	0.94	-0.067
IDW	0.75	-0.004

OK: Ordinary kriging; COK: Cokriging; IDW: Inverse distance weighting

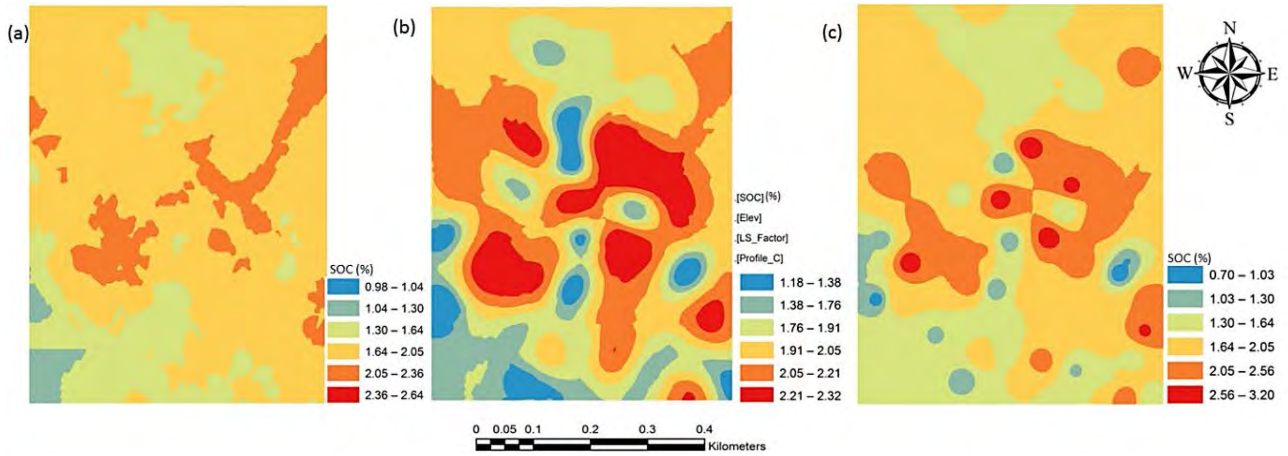


Fig. 4. SOC(%) prediction maps via (a) OK model (b) COK model (c) IDW model

3.6. Descriptive statistics of predicted soil organic carbon (SOC)

The summary statistics of the predicted SOC by the three different models are presented in Table 4. The predicted SOC values also presented a normal distribution for the interpolation methods. SOC predicted value was 1.68% for OK, COK, and IDW, respectively. Also, the measure SOC minimum and maximum value were the same as that of IDW prediction.

The descriptive statistics of the predicted SOC values showed a normal distribution like the measured SOC. The result is supported by the report of Chabala et al. (2017). Despite that, the work revealed that SOC predicted was lower than SOC measured value. And when compared to Landon (1991) ratings, predicted SOC was observed to be very low (< 2 %). This shows that this level of SOC cannot sustain an intensive cropping system in the area. The result obtained here may be attributed to lumbering activities often carried out in the area.

Table 4. Predicted SOC using OK, COK and IDW

	Mean	*Min*	*Max*	*SD*	*CV*	*skewness*	*kurtosis*
OK	1.68	0.98	2.64	0.27	16.1	0.54	-0.05
COK	1.68	1.18	2.32	0.37	22	0.33	-0.33
IDW	1.68	0.7	3.2	0.52	31	0.88	0.91

This action results in significant losses of SOC, which tend to reduce further crop yields under continuous cultivation. This act of deforestation would further lead to the decline in soil fertility through increased soil erosion, reduction of litter influx after canopy removal and boosted decomposition and nutrient mineralization rates after forest clearance.

4. Conclusions

In this present study, OK, COK and IDW interpolations were performed and compared to evaluate the accuracy of our prediction of the geographical variability SOC.

The study revealed that SOC was generally low in the research site. SOC demonstrated a moderate spatial dependence and explained the essence of estimating SOC spatial variability in southeastern Nigeria. Among the three interpolations, IDW was the best performing model. At the same time, the COK model gave the smallest mean error, which was observed to have occurred due to terrain attributes. The predicted SOC map by COK with Elev, LS-F and profile C covariates improved the OK and IDW maps, respectively. The COK map was more detailed, showing the capability of terrain attributes being robust ancillary variables for improving detailed spatial SOC maps.

In conclusion, the SOC created maps by COK and IDW of the study area could be adopted by both soil and land users to help grow different crops concerning their different nutrient needs for adequate agricultural production management. Besides that, the created maps could be used as a reference point for various soil purposes, ranging from sampling optimization to updating soil maps with more ancillary variables. Furthermore, for future studies, it is recommended that different auxiliary covariates be introduced and an increase in sample density to improve the accuracy of the models in estimating SOC.

Acknowledgements

Mr Kingsley John Funding This study was supported by an internal PhD grant no. SV20-5-21130 of the Faculty of Agrobiology, Food and Natural Resources of the Czech University of Life Sciences Prague (CZU). Secondly, the Czech Science Foundation projects no. 17–277265 (Spatial prediction of soil properties and classes based on position in the landscape and other environmental covariates) and 18–28126Y (Soil contamination assessment using hyperspectral orbital data) for the financial support. Thirdly, the Centre of Excellence (Centre of the investigation of synthesis and transformation of nutritional substances in the food chain in interaction with potentially risk substances of anthropogenic origin: comprehensive assessment of the soil contamination risks for the quality of agricultural products, NutRisk Centre) and the European project no. CZ.02.1.01/0.0/0.0/16_019/0000845.

References

Abua M., Eyo E., (2013), Assessment of soils around quarry terrain in Akamkpa local government area, Cross River State-Nigeria, *Merit Research Journal of Agricultural Science and Soil Sciences*, **1**, 001-005.

Aki E.E., Esu I.E., Akpan-Idiok A.U., (2014), Pedological study of soils developed on Biotite- Hornblende-Gneiss in Akamkpa Local Government Area in Cross River State, Nigeria, *International Journal of Agricultural Research*, **9**, 187-199.

Akpa S.I.C., Odeh I.O.A., Bishop T.F.A., Hartemink AE, (2014), Digital mapping of soil particle-size fractions for Nigeria, *Soil Science Society of America Journal*, **78**, 1953-1966.

Ayito E.O., Iren O.B., John K., (2018), Effects of neem-based organic fertilizer, NPK and their combinations on soil properties and growth of Okra (*Abelmoschus esculentus*) in a Degraded Ultisol of Calabar, Nigeria, *International Journal of Plant & Soil Science*, **25**, 1-10.

Brodsky L., Vasat R., Klement A., Zadorova T., Jaksık O., (2013), Uncertainity propagation in VNIR reflectance spectroscopy of soil organic carbon mapping, *Geoderma*, **199**, 54-63.

Bhunia S.G., Shit PK, Maiti R., (2016), Comparison of GIS-based interpolation methods for spatial distribution of soil organic carbon (SOC), *Journal of the Saudi Society of Agricultural Sciences*, **17**, 114-126.

Bivand R.S., Pebesma E.J., Gomez-Rubio V., (2008), *Applied Spatial Data Analysis with R*, Springer, New York.

Bishop T.F.A., McBratney A.B., (2001), A comparison of prediction methods for the creation of field-extent soil property maps, *Geoderma*, **103**, 149-160.

Bolliger A., Magid J., Amado J.C.T., Neto F.S., dos Santos Ribeiro M.D.F., Calegari A., Ralisch R., de Neergaard A., (2006), Taking stock of the Brazilian "Zero - Till Revolution": A review of landmark research and farmers' practice, *Advances in Agronomy*, **91**, 47-110.

Cambardella C., Moorman T., Parkin T., Karlen D., Novak J., Turco R., Konopka A., (1994), Field-scale variability of soil properties in central Iowa soils, *Soil Science Society of America Journal*, **58**, 1501-1511.

Cerri C.C., Bernoux M., Arrouays D., Feigl B.J., Piccolo M.C., (2000), *Carbon Stocks in Soils of the Brazilian Amazon,* In: *Global Climate Change and Tropical Ecosystems*, Lal R., Kimble J.M., Stewart B.A., (Eds), CRC Press, Boca Raton, 33-50.

Chabala L.M., Mulolwa A., Lungu O., (2017), Application of ordinary kriging in mapping soil organic carbon in Zambia, *Pedosphere*, **27**, 338-343.

Fang X., Xue Z., Li B., An S., (2012), Soil organic carbon distribution in relation to land use and its storage in a small watershed of the Loess Plateau, China, *Catena*, **88**, 6-13.

Forkuor G., Hounkpatin O.K.L., Welp G., Thiel M., (2017), High-resolution mapping of soil properties using remote sensing variables in south-western Burkina Faso: a comparison of machine learning and multiple linear regression models, *PLoS One*, **12**, 0170478, https://doi.org/10.1371/journal.pone.0170478.

Goovaerts P., (1997), *Geostatistics for Natural Resources Evaluation*, Oxford University Press, New York, USA.

Gregorich E.G., Carter M.R., Angers D.A., Monreal C.M., Ellert B.H., (1994), Toward minimum data set to assess soil organic matter quality in agricultural soils, *Canadian Journal of Soil Science*, **74**, 885-901.

Grunwald S., Osborne T.Z., Reddy K.R., (2008), Temporal trajectories of phosphorus and pedo-patterns mapped in Water Conservation Area 2, Everglades, Florida, USA, *Geoderma*, **146**, 1-13.

Gubiani P.I., Reichert J.M., Reinert D.J., Gelain N.S., (2011), Implications of the variability in soil penetration resistance for statistical analysis, *Revista Brasileira de Ciência do Solo*, **35**, 1491-1498.

John K., Ayito E.O., Odey S., (2018), Interaction between some soil physicochemical properties and weather variables on sub-humid tropical rainforest soils of cross river state, Southeastern Nigeria, *Annual Research & Review in Biology*, **29**, 1-12.

John K., Solomon O.L., Ayito E.O., Ndiye M.K., Ogeh J.S., Vít P., (2019a), Predictive mapping of soil properties for precision agriculture using geographic information system (GIS) based geostatistics models, *Modern Applied Science*, **13**, 60-74.

John K., Akpan-Idiok A.U., (2019b), Land evaluation, characterization and classification of soil for the proposed oil palm plantation in Ekpri Ibami, Akamkpa Local Government Area, Nigeria, *International Journal of Environment Agriculture and Biotechnology*, **4**, 621-634.

Kumar S., Lal R., Liu D., Rafiq R., (2013), Estimating the spatial distribution of organic carbon density for the soils of Ohio, USA, *Journal of Geographical Sciences*, **23**, 280-296.

Kozłowski M., Komisarek J., (2018), Influence of terrain attributes on organic carbon stocks distribution in soil toposequences of central Poland, *Soil Science Annual*, **69**, 215-222.

Landon J.R., (1991), *Booker Tropical Soil Manual*, Longman Scientific and Technical Essex, UK.

Larsen E., Grossman J., Edgell J., Hoyt G., Osmond D., Hu S., (2014), Soil biological properties, soil losses and corn yield in long-term organic and conventional farming systems, *Soil Tillage Research*, **139**, 37-45.

Li X., McCarty G., Karlen D., Cambardella C., (2018), Topographic metric predictions of soil redistribution and organic carbon in Iowa cropland fields, *Catena*, **160**, 222-232.

Li J., Heap A.D., (2008), A review of spatial interpolation methods for environmental scientists, Canberra, Australia: Geoscience Australia, Record 2008/23, 137-154.

Liu L., Wang H., Dai W., Lei X., Yang X., Li X., (2014), Spatial variability of soil organic carbon in the forestlands of northeast China, *Journal of Forest Research*, **25**, 867-876.

Liu W., Hai-Rong Z., Da-Peng Y., Sheng-Li W., (2017), Adaptive Surface Modeling of Soil Properties in Complex Landforms, *ISPRS International Journal of Geo-Information*, **6**, 178, https://doi.org/10.3390/ijgi6060178.

McBratney A.B., Mendoça-Santos M.L., Minasny B., (2003), On digital soil mapping, *Geoderma*, **117**, 3-52.

Mohammad, Z.M., Taghizadeh-Mehrjardi R., Akbarzadeh, A., (2010), evaluation of geostatistical techniques for mapping spatial distribution of soil pH, salinity and plant cover affected by environmental factors in Southern Iran, *Notulae Scientia Biologicae*, **2**, 92-103.

Mondal A., Khare D., Kundu, S., Mondal S., Mukherjee S., Mukhopadhyay A., (2016), Spatial soil organic carbon (SOC) prediction by regression kriging using remote sensing data, *The Egyptian Journal of Remote Sensing and Space Sciences*, **20**, 61-70.

Morris S.B., (2007), *Book Review*: Hunter J.E., Schmidt F.L., (2004), Methods of Meta-Analysis: Correcting Error and Bias in Research Findings, 2nd Edition,

Thousand Oaks, CA: Sage, *Organizational Research Methods*, **11**, 184-187.
NiMet, (2015), Annual meteological reading at Calabar Station, Nigerian Metrological Station, On line at: https://www.nimet.gov.ng/.
Olaya V., (2004), A Gentle Introduction to SAGA GIS, On line at: https://freecomputerbooks.com/A-Gentle-Introduction-to-SAGA-GIS.html.
Pang S., Li T.X., Zhang X.F., Wang Y.D., Yu H.Y., (2011), Spatial variability of cropland lead and its influencing factors: A case study in Shuangliu County, Sichuan province, China, *Geoderma*, **162**, 223-230.
Philip G.M., Watson D.F., (1982), A precise method for determining contoured surfaces, *Australian Petroleum Exploration Association Journal*, **22**, 205-212.
Piccini C., Marchetti A., Francaviglia R., (2014), estimation of soil organic matter by geostatistical methods: use of auxiliary information in agricultural and environmental assessment, *Ecological Indicator*, **36**, 301-314.
Robinson T.P., Metternicht G., (2006), Testing the performance of spatial interpolation techniques for mapping soil properties, *Computer Electronics and Agriculture*, **50**, 97-108.
Saleh A.M., (2018), Spatial variability mapping of some soil properties in Jadwal Al_Amir Project/Babylon/Iraq, *Journal of the Indian Society of Remote Sensing*, **46**, 1481-1495.
Sanderman J., Farquharson R., Baldock J.A., (2010), *Soil Carbon Sequestration Potential*, A review for Australian agriculture, CSIRO Sustainable Agriculture Flagship Report, prepared for Department of Climate Change and Energy Efficiency, On line at: www.csiro.au/resources/ Soil-Carbon-Sequestration-Potential-Report.html.
Stein A., Corsten LCA, (1991), Universal kriging and cokriging as regression procedure, *Biometrics*, **47**, 575-587.
Triantafilis J., Odeh I.O.A., Mcbratney A.B., (2001), Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton, *Soil Science Society of America Journal*, **65**, 869-878.
Tsui C., Chen-Chi T., Zueng-Sang C., (2013), Soil organic carbon stocks in relation to elevation gradients in volcanic ash soils of Taiwan, *Geoderma*, **210**, 119-127.
Tziachris P., Eirini M., Frantzis P., Maria P., (2017), Spatial modelling and prediction assessment of soil iron using kriging interpolation with pH as auxiliary information, *ISPRS International Journal of Geo-Information*, **6**, 283, https://doi.org/10.3390/ijgi6090283.
Udo E.J., Ibia T.O., Ogunwale J.A., Ano AO, Esu IE, (2009), *Manual of Soil, Plant and Water Analysis*, Sibon Books Publishers Ltd, Nigeria.
USDA-NRCS, (1995), Soil Survey Laboratory Information Manual, Soil Survey Investigations Report No. 45. National Soil Survey Center, Soil Survey Laboratory, United States Department of Agriculture-Natural Resources Conservation Service, Lincoln, Nebraska.
Wiesmeier M., Barthold F., Spörlein P., Geuß U., Hangen E., Reischl A., (2014), estimation of total organic carbon storage and its driving factors in soils of Bavaria (southeast Germany), *Geoderma Regional*, **1**, 67-78.
Wang Y., Fu B., Yi H.L., Song C., Luan Y., (2010), Local-scale spatial variability of soil organic carbon and its stock in the hilly area of the Loess Plateau, *China Quaternary Research*, **73**, 70-76.
Wei J.B., Xiao D.N., Zeng H., Fu Y.K., (2008), Spatial variability of soil properties in relation to land use and topography in a typical small watershed of the black soil region, northeastern China, *Environmental Geology*, **53**, 1663-1672.
Wu C., Jiaping W., Yongming L., Limin Z., Stephen D., (2009), Spatial prediction of soil organic matter content using cokriging with remotely sensed data, *Soil Science Society of America Journal*, **73**, 1202-1209.
Yang Q., Jiang Z., Ma Z., Li H., (2014), Spatial prediction of soil water content in karst area using prime terrain variables as auxiliary cokriging variable, *Environmental Earth Sciences*, **72**, 4303-4310.
Yang Y., Zhu J., Tong X., Wang D., (2009), *Spatial Pattern Characteristics of Soil Nutrients at the Field Scale*, Li D., Zhao C. (Eds.), *Computer and Computing Technologies in Agriculture*, Springer, Berlin, Heidelberg, 125-134.
Zhang G., Liu F., Song X., (2017), Recent progress and future prospect of digital soil mapping: A review, *Journal of Integrative Agriculture*, **16**, 2871-2885.
Zhu A.X, Liu F., Li B.L., Pei T., Qin C.Z., Liu G.H., Wang Y.J., Chen Y.N., Ma XW, Qi F., Zhou C.H., (2010), Differentiation of soil conditions over flat areas using land surface feedback dynamic patterns extracted from MODIS, *Soil Science Society of America Journal*, **74**, 861-869.